Using Social Comparisons to Facilitate Healthier Choices in Online Grocery Shopping Contexts

Blake DiCosola
Oxford Internet Institute
University of Oxford
Oxford, OX1 3JS, UK
Blake.DiCosola@oii.ox.ac.uk

Gina Neff
Oxford Internet Institute
University of Oxford
Oxford, OX1 3JS, UK
Gina.Neff@oii.ox.ac.uk

CHI 2020 Extended Abstracts, April 25–30, 2020, Honolulu, HI, USA.

ACM ISBN 978-1-4503-6819-3/20/04.
https://doi.org/10.1145/3334480.3382877

Abstract
This exploratory research examines how we might nudge consumers towards making healthier food choices in online grocery shopping or other digitally mediated food consumption contexts. Our pilot study investigated how different forms of social comparisons could be used to encourage consumers to reduce the number of calories contained in their online grocery basket. Our findings show that participants who were less interested in trying new diets were more willing to reduce calories when presented with a comparison to people unlike them, an out-group member comparison, while those who were interested in trying new diets were more willing to reduce calories regardless of social comparison type. These findings imply that one size does not fit all when nudging. More research is needed to see how social comparisons influence the effectiveness of digital health behavior projects.

Author Keywords
Consumer behavior; choice; decision making; nudging; persuasive communication; social influence; food; diet; health; nutrition; online; digital; shopping; intervention

CSS Concepts
• **Human-centered computing** → **Human computer interaction (HCI);** Empirical studies in HCI

Introduction

The human-computer interaction (HCI) community has been interested in the effective and ethical use of design to create architectures for encouraging and supporting people's choices across a range of behaviors [5]. Thaler and Sunstein show how people can be 'nudged' [15] by altering choice environments and architectures, making it easier for people to make choices that they think are better for them, their families and society. Not surprisingly, given the pressing nature of the global obesity crisis and the promise of nudging, there has been much research by consumer psychologists, behavioral economists and public health scientists on modifying choice architectures in physical food choice environments, such as traditional brick-and-mortar grocery stores and cafes, to encourage healthier food choices [3]. Governments and public health groups too have embraced experimenting with nudging for the public good [17]. However, given the interest in designing environments that support healthy choices, the HCI community still has many open questions about what types of designs work best. Self-tracking and nudge research has suffered from what Ackerman described as the social-technical gap between what researchers can support technically and the social needs or requirements of groups [1,6]. When looking at people's attitudes and experiences of tracking, new kinds of motivations surface, from users' experience between the gap between incentives and more holistic views of health [6] to the competing logics beyond productivity, efficiency and optimization that shape people choices [9,14]. Still, studies are designed to encourage peer support in behavior change, e.g. [13] based on an assumption that social support and community sensemaking [12] matter for success. What if a sense of community was not the primary factor that drove people's responsiveness to the social cues of nudging?

Our pilot study expands existing CHI research by asking what kinds of nudges work in digital food choice environments, such as rapidly growing online grocery shopping channels [11]. Specifically, we test whether the design of social comparisons makes a difference in people's choices. Our work compliments existing work by scholars in HCI related to nudge and the design of effective online diet interventions [5,8]. We add the element of measuring if social comparisons make a difference in people's choices and if so, what type of comparison might be more effective in this situation.

Experiment Overview

We tested whether different types of social comparisons could be used to nudge consumers to reduce the number of calories in their online grocery basket or shopping cart. While it has become relatively commonplace for social comparisons in online contexts to rely solely on in-group comparisons (i.e. 'people like you' comparisons) [2], this pilot study introduces *out-group* comparisons. Our research suggests that, when framed appropriately, out-group comparisons may work better than in-group comparisons for eliciting favorable choices.

We conducted a simple online experiment with a single factor (social comparison) and two levels (in-group comparison, out-group comparison) on Qualtrics to test the hypothesis that out-group comparisons may be equally or more effective than in-group comparisons in encouraging healthier choices. Our pilot study was designed to test a conceptual intervention that could be applied to broad populations to help prevent obesity

before it starts when a shopping cart detects abnormal trends that could result in over-consumption; future studies will look at overweight populations and focus on obesity reduction through behavior change.

We recruited 100 healthy-weight adults living in the United Kingdom (UK) from an online panel designed for academic research, Prolific.co. Participants were contacted via e-mail through Prolific and notified they could participate in a four-minute online study on health and nutrition in the UK. Participants were offered a payment of £0.50 for their participation in this short study.

Sample Size	100 Healthy-Weight UK Adults (BMI<25)
Study Design	Single Factor, Two-Level, Between Subjects
Study Factor	Social Comparison
Study Levels	In-Group, Out-Group

Table 1: Pilot Study Summary

After giving their consent, participants were asked to complete a 1–2-minute online survey on health, fitness, and nutrition. The survey contained 10 questions, including a key question that asked participants to rate their interest in trying new diets on a sliding scale (0 = no interest, 100 = high interest). Then, participants were asked to imagine that they were buying groceries from an online grocery store where they had previously setup a profile to allow the grocery store to know their specific health and nutrition goals. Participants were then asked to imagine they were buying one week's worth of groceries and were about to complete the online checkout process.

At this point, participants were randomly assigned to one of the two experimental conditions. In both experimental conditions, participants were shown a prompt at checkout that informed them that they were projected to consume a weekly caloric surplus that would result in weight gain (i.e. 3,500 extra calories). Participants' weekly caloric was compared to other 'healthy adults like you' in the in-group condition and to 'overweight adults' in the out-group condition. All other text, numbers, and graphical elements remained the same and were held constant across both conditions (See Fig.1).

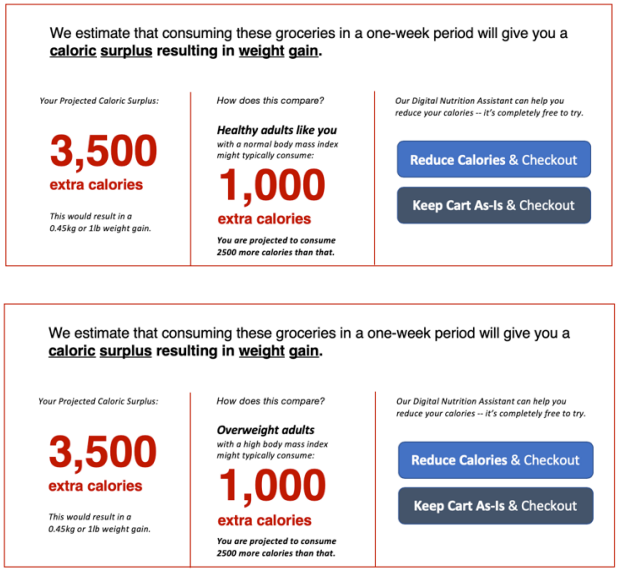

Figure 1: Experimental Condition Stimuli

Participants were then asked to make a discrete choice: they could either elect to keep their shopping cart as-is and checkout or to reduce the calories in their cart and checkout using a free digital nutrition assistant. This choice is the key dependent measure used in subsequent statistical analyses.

Individuals who elected to reduce calories were asked a follow-up question related to the number of total calories they wished to reduce their cart by—they indicated this by using a sliding scale from 0 calories to 5000 calories. After completing this step, all participants were shown a closing page that debriefed them and revealed more details about the study; participants were also provided with a code that was passed to Prolific to confirm study completion and initiate payment of £.50 for participation in the study.

The last page of the experiment also included a manipulation check that asked participants to recall what type of individual they were compared to. Twenty-six participants failed the manipulation check and were removed from the study results, leaving 74 possible valid observations in the experimental data set. Nine individuals identified as overweight or underweight, rather than normal or healthy weight as specified in the screener, and thus omitted from the study so that only healthy weight adults were included per the recruitment screener and survey check.

Experiment Results

In the end, there were 65 valid responses that could be analyzed after data cleansing was complete. VanVoorhis & Morgan [16] indicate that when conducting statistical analyses to measure group differences a reasonable cell size is 30, assuming a power level threshold of 80%. As such, the final cleansed data set with 65 observations was used for all analyses, although the total number of observations after cleansing was less than optimal.

A statistical model that included the key discrete dependent measure (choice: unhealthy/keep cart as-is and checkout vs. healthy/reduce calories and checkout) along with two independent variables—level of interest in trying new diets and social comparison type (in-group vs. out-group)—was established. A nominal logistic regression analysis was conducted on the model. The overall model was found to be highly significant, X^2 (3, n = 65) = 15.62, p = .0014. The coefficient of determination (R^2) value of the model was .1770 (17.70%), indicating that we have identified a medium to large experimental effect within this statistical model [7].

Overall Statistical Model

Chi-Square Value	X^2 (3, n = 65) = 15.62
p-Value	p = .0014
R^2 Value	R^2 = .1770 (17.70%)

Table 2: Overall Statistical Model Summary

There was a significant main effect of level of interest in trying new diets on unhealthy/healthy choice, X^2 (3, n = 65) = 4.68, p = .03, such that those who were more interested in trying new diets were more likely to select the healthier option, which is intuitive and not all that surprising (See Table 3). That said, there was a more significant interaction effect between level of interest in

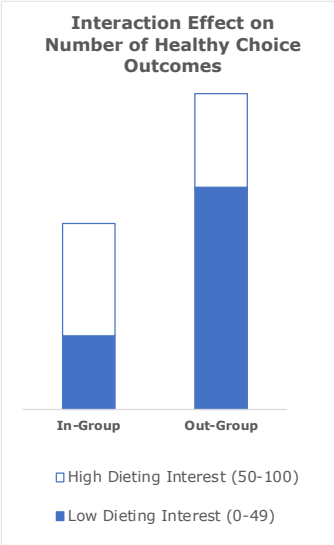

Figure 2: Interaction Effect

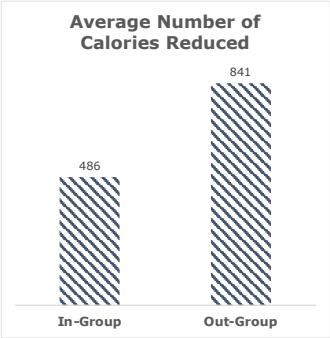

Figure 3: Mean Calorie Reduction

trying new diets and the type of social comparison used, X^2 (3, n = 65) = 7.50, p = .006, such that those who were less interested in trying new diets (and thus more at-risk for over-consuming) but assigned to the out-group condition were now more likely to reduce calories (See Fig. 2, Table 5).

Main Effect: Interest in Trying New Diets (IV1)	
Chi-Square Value	X^2 (3, n = 65) = 4.68
p-Value	p = .03

Table 3: Main Effect of Interest in Trying New Diets

Main Effect: Social Comparison Type (IV2)	
Chi-Square Value	X^2 (3, n = 65) = 2.67
p-Value	p = .10

Table 4: Main Effect of In-Group vs. Out-Group Comparison

Interaction Effect: IV1 x IV2	
Chi-Square Value	X^2 (3, n = 65) = 7.50
p-Value	p = .006

Table 5: Interaction Effect (IV1 x IV2)

The main effect of social comparison type did not prove to be statistically significant (See Table 4), X^2 (3, n = 65) = 2.67, p=.10. However, the pattern of results indicated that healthy choice outcomes were more abundant in the out-group condition. An analysis of variance (ANOVA) using the continuous measure of calorie reduction revealed the mean number of calories reduced in the in-group condition was 486 compared to 841 in the out-group condition (See Fig. 3), which provides some baseline support for our hypothesis that out-group comparisons may be as effective if not more effective than the more frequently used in-group comparisons. However, the difference between social comparison types was not found to be statistically significant in the ANOVA model either.

Discussion

Our pilot study revealed two statistically significant findings. There was an overall main effect of level of interest in trying new diets on healthy choice outcomes across both social comparison conditions. In addition, there was a stronger interaction effect between people's interest in dieting and the type of social comparison that was used.

The results indicate that the nutritional cart summary with social comparison was an effective intervention among people who are open to trying new diets, regardless of whether they were shown comparisons to people like or unlike them. That said, the lack of a no comparison control condition in this simple pilot study limits our ability to decipher whether this effect is due to the social comparison element of our experimental stimuli. We will address this limitation in future studies.

The interaction effect that we observed seems to indicate that we have identified a novel way to reach people who are not interested in trying new diets. Our findings show that a shopping cart nutritional analysis paired with an out-group comparison—rather than the

standard 'people like you' comparison—resulted in an increase in the healthier choice options among those who reported that they were not interested in trying new diets.

It is worth noting the medium-to-large effect size we observed with our overall model returning an R^2 value of .1770 or 17.70% (See Table 6).

	Effect Size		
Measure	Small	Medium	Large
Cohen's *d*	0.2 - 0.3	≈ 0.5	0.8
R^2	1%	9%	25%

Table 6: Effect Size Comparison [7]

In Cadario and Chandon's meta-analysis of field studies exploring healthy eating nudges taking place in traditional brick-and-mortar settings [3], the researchers found that the effect sizes for healthy eating nudges were small, on average, across all seven studies they looked at. The medium-to-large effect size we observed in our online experiment points to the potential promise of digital nudging to influence healthier food choices.

While our pilot study revealed some promising results, there are numerous shortcomings that must be addressed. It is important to note that we recruited adults with a body mass index of under 25 in order to be able to assign participants to an in-group (i.e. healthy adults) or out-group (i.e. overweight adults), and as such we cannot over-generalize our findings and assume these results would be observed among overweight adults, given that we know from previous research in public health that healthy adults and overweight adults often exhibit different responses to nutrition interventions [4,10]. Different goals may require different designs, especially in health-related tracking [14], and this context is no different.

To address this shortcoming, a follow-up study will be run on participants with a body mass index over 25 who view themselves as being overweight and will provide an in-group comparison to overweight adults and an out-group comparison to healthy-weight adults. We will also add a no comparison control condition and also increase the sample size moving forward, as those are two other key limitations we note in our current pilot.

All in all, we believe our pilot study shows the promise of online nudging through the use of social comparisons in online grocery shopping contexts. Future studies will investigate whether nudges that are based on automated self-comparisons (comparisons to past versions of the self and comparisons to the ideal future self) might also be effective, knowing people have a long history of and interest in tracking themselves and monitoring progress [12]. In addition, we will look to see if comparing individual behavior to benchmarked standards from credible, well-known sources (such as USDA MyPlate or NHS EatWell) might further improve intervention participation. Our pilot suggests that there is much work to be done and that designers should further consider the social as well as technical configurations of nudging to inspire healthier choice outcomes.

References

[1] Mark S. Ackerman. 2000. The Intellectual Challenge of CSCW: The Gap Between Social Requirements and Technical Feasibility. *Human–Computer Interaction* 15, 2–3 (September 2000), 179–203. DOI:https://doi.org/10.1207/S15327051HCI1523_5

[2] Alexander Benlian, Ryad Titah, and Thomas Hess. 2012. Differential effects of provider recommendations and consumer reviews in e-commerce transactions: An experimental study. *Journal of Management Information Systems* 29, 1 (July 2012), 237–272. DOI:https://doi.org/10.2753/MIS0742-1222290107

[3] Romain Cadario and Pierre Chandon. 2019. Which Healthy Eating Nudges Work Best? A Meta-Analysis of Field Experiments. *Marketing Science* (July 2019). DOI:https://doi.org/10.1287/mksc.2018.1128

[4] Sarah Campos, Juliana Doxey, and David Hammond. 2011. Nutrition labels on pre-packaged foods: A systematic review. *Public Health Nutrition 14*, 1496–1506. DOI:https://doi.org/10.1017/S1368980010003290

[5] Ana Caraban, Instituto Superior Técnico, Evangelos Karapanos, Daniel Gonçalves, and Pedro Campos. 23 Ways to Nudge: A Review of Technology-Mediated Nudging in Human-Computer Interaction. 15. DOI:https://doi.org/10.1145/3290605.3300733

[6] Chia-Fang Chung, Nanna Gorm, Irina A. Shklovski, and Sean Munson. 2017. Finding the Right Fit: Understanding Health Tracking in Workplace Wellness Programs. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI '17*, ACM Press, Denver, Colorado, USA, 4875–4886. DOI:https://doi.org/10.1145/3025453.3025510

[7] Steve Draper. Effect size. http://www.psy.gla.ac.uk/~steve/best/effect.html

[8] Jill Freyne, Ian Saunders, Emily Brindal, Shlomo Berkovsky, and Gregory Smith. 2012. Factors associated with persistent participation in an online diet intervention. Association for Computing Machinery (ACM), 2375. DOI:https://doi.org/10.1145/2212776.2223805

[9] Nanna Gorm and Irina Shklovski. 2019. Episodic use: Practices of care in self-tracking. *New Media & Society* 21, 11–12 (November 2019), 2505–2521. DOI:https://doi.org/10.1177/1461444819851239

[10] Erica van Herpen and Hans C.M.van Trijp. 2011. Front-of-pack nutrition labels. Their effect on attention and choices when consumers have varying goals and time constraints. *Appetite* 57, 1 (August 2011), 148–160. DOI:https://doi.org/10.1016/j.appet.2011.04.011

[11] Sanjeev Meena, Satish; Swerdlow, Fiona; Kumar. The State Of Global Online Grocery Retail, 2018. https://www.forrester.com/report/The+State+Of+Global+Online+Grocery+Retail+2018/-/E-RES143057#

[12] Gina Neff and Dawn Nafus. 2016. *Self-tracking*. MIT Press.

[13] Xipei Ren, Bin Yu, Yuan Lu, and Aarnout Brombacher. 2018. Exploring Cooperative Fitness Tracking to Encourage Physical Activity among Office Workers. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (November 2018), 1–20. DOI:https://doi.org/10.1145/3274415

[14] Katta Spiel, Fares Kayali, Louise Horvath, Michael Penkler, Sabine Harrer, Miguel Sicart, and Jessica Hammer. 2018. Fitter, Happier, More Productive?: The Normative Ontology of Fitness Trackers. In *Extended Abstracts of the 2018 CHI Conference on*

Human Factors in Computing Systems - CHI '18, ACM Press, Montreal QC, Canada, 1–10. DOI:https://doi.org/10.1145/3170427.3188401

[15] Richard H Thaler and Cass R Sunstein. 2008. *Nudge : improving decisions about health, wealth, and happiness*. Yale University Press, New Haven, Conn.

[16] Carmen R Wilson VanVoorhis and Betsy L Morgan. 2007. *Understanding Power and Rules of Thumb for Determining Sample Sizes*.

[17] Publications | The Behavioural Insights Team. https://www.bi.team/our-work/publications/